Consumer Choice and Environmental Policies: Evidence on the Role of Product Substitutes from a Field Experiment*

Bruno Lanz† Jules-Daniel Wurlod‡ Luca Panzone§ Timothy Swanson†

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Abstract

This paper employs real purchasing decisions observed during a field experiment to examine consumer choices in response to alternative environmental policy interventions: a carbon-footprint label, a monetary instrument and a regulatory ban. We consider a range of commonly purchased products, manipulating the choice set of consumers initially purchasing 'clean' or 'dirty' products. We explore whether the existence of close substitutes matters for the effectiveness of policy instruments to regulate the public good by using two environmentally 'neutral' treatments as implicit measures of how substitutable clean and dirty versions are, namely a price reduction for clean products (an implicit price elasticity) and a neutrally framed removal of the dirty product as a measure of the propensity of consumers to exit the market when their preferred option is removed from the choice set. Applying a Random Utility framework, we find that, while all instruments significantly increase the market share of the clean products – on average from 16-24% – regulatory, information-based and monetary instruments perform better when the clean alternative is a good substitute to the dirty, i.e. the private cost of switching to the clean alternative is moderate. Furthermore, motivation crowding effects of monetary incentives on voluntary participation seem to be stronger in the presence of close substitutes. The absence of substitutes acts as a 'preference constraint' lowering both the effectiveness of policies to regulate the public good *on average* and crowding-out effects.

Keywords: Field experiments; Instrument choice; Market-based instruments; Information provision; Product choice.

JEL Codes: C25; D12; D64; Q58.

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†Graduate Institute Geneva, Switzerland.

‡Graduate Institute Geneva, Switzerland. E-mail: jules-daniel.wurlod@graduateinstitute.ch (corresponding author) Tel: +41/79.664.53.27.

§School of Agriculture, Food and Rural Development, Newcastle University.

1 Introduction

Policy interventions to regulate the provision of public goods in general and environmental externalities in particular can take different forms: market-based instruments such as taxes and subsidies, direct regulation and standards, and information provision favoring voluntary contributions. While there are good theoretical arguments favoring market-based instruments for their efficiency property, in practice a number of important question remain open. Are market based-instrument crowding out the willingness to contribute to public goods? Can information provision through labels induce voluntary contributions that are comparable to market-based instruments? If governments intervene directly on markets by banning some products, do consumers redirect their choice towards 'cleaner' goods, or simply exit the market? In particular, there is little evidence about how similar policy instruments influence consumption choices across different products and whether the existence of 'clean' products that are close substitutes will impact their effectiveness.

Our experiment, described in details in Panzone et al. (2011) and in Perino et al. (2014), offers the possibility to consumers to revise an initial consumption choice in a supermarket after being subject to one of five policy treatments. The advantage of this dataset is to include multiple products and multiple policy instruments in a single framework, offering the possibility to investigate how characteristics of products and policy instruments interact for determining consumption choices. Panzone et al. (2011) have used this experiment to compare the effectiveness of policy instruments. Perino et al. (2014) have tested specifically motivation crowding mechanisms by comparing the impact of a subsidy with first an information label and second a neutrally framed price change. The present piece of work complements these studies by modeling explicitly the role of the cost of switching from dirty to clean alternatives. We make appropriate use of neutrally framed treatments to recover a measure of substitutability directly estimated from a revealed preference setting. This allows to observe whether the existence of close substitutes affects the effectiveness of policy instruments to regulate the public good and/or motivation crowding effects. Another key contribution comes from the use of a Random Utility Modeling (RUM) framework (Lancaster, 1966). The structural representation of choice behavior afforded by the RUM framework provides a rich basis to understand consumers' response across goods and treatments. More specifically, the multinomial logit (MNL) used to estimate our model al-

lows to identify tastes for characteristics of products and observe how these interact with public attributes.[1]

While the availability of close substitutes should matter in theory and could seem trivial, empirical evidence on its role for the effectiveness of policies aiming a redirecting consumers choices is rather scarce. One major reason is that empirical tests of substitution patterns requires choice sets to be controlled and finite. When using real market data, substitution patterns cannot be precisely identified because some options are unobserved. Substitutes to, say, Cola-type sodas in cans, can range from Cola in other packaging, to other types of sodas, or even other beverages. Studies using real market data have overcome this issue by using ad-hoc assumptions and considering only subgroups of products (see for example Bjorner et al., 2004; Teisl et al., 2008; Vanclay et al., 2011; Michaud et al., 2013). In contrast, our data is generated from a controlled experiment that offers an exhaustive set of options to consumers, such that we can model directly the substitution among clean and dirty options based on their underlying attributes and consumers' tastes for these, without additional assumptions. Moreover, our study uses revealed preferences, thereby avoiding the gap between intentions and actions (Gollwitzer and Brandstaetter, 1997; Carrington et al., 2010; Bray et al., 2011), which may be an issue with stated preferences, especially in the context of participation to the public good where an "Ethical Purchasing Gap" has been found to be important (Cowe and Williams, 2000; Nicholls and Lee, 2006).

Information on the public good content of goods, as provided by the labeling treatment, has a dual role. First, it increases consumer awareness and decreases the search cost for information. Consumers are thereby more aware of the environmental impacts associated with their choices, which helps them to match their preferences better by making unobservable characteristics observable - turning 'credence' goods into 'search' goods (Cohen and Vandenbergh, 2012). Hence, labeling may affect behavior by providing one more observable characteristic or attribute to the goods on the market. Second, the impact of labeling will depend on the tastes for the environmental attribute, which will change consumers' valuation of the good (Teisl et al., 2002). This is mainly driven by the existence of individual-specific weightings of public vs. private goods

[1] The MNL model is convenient for its tractability. However, the well-known the "irrelevance of independent alternatives" property of this model is unlikely to hold in most settings. In a second step, we estimate a Mixed Logit model that is more general as robustness check.

attributes, which has long been recognized in the literature (Harsanyi, 1955; Margolis, 1982; Nyborg, 2000). In practice, the disclosure of environmental information in general, and through eco-labels in particular, has become an important policy tool, and the number of standards for "green" products has increased in recent years (US EPA, 2013).[2]

Our study is related to the growing body of empirical evidence on the effectiveness of carbon labels on consumption behavior. Several market-based studies have found a potential for eco-labels to affect market outcomes (Blamey and Bennett, 2001; Bjorner et al., 2004; Teisl et al., 2002). Bjorner et al. (2004) have identified a positive effect of the "Nordic Swan" environmental label on willingness-to-pay for consumers. Using a large Danish consumer panel from 1997 to 2001, the authors find that the label has had a "significant effect on consumers' brand choices for toilet paper, corresponding to a marginal willingness to pay for the certified environmental label of 13-18%". In our study, an information-based instrument results in an increase in predicted market share from 6-15% percent depending on the type of good considered. Teisl et al. (2002) have also found a positive market reaction to eco-labels using data on the consumption of "Dolphin-friendly" canned tuna in the US. Henion (1972) has found that labels on the content of phosphates had an impact on the demand for detergents in a real market experiment. Blamey and Bennett (2001), Bennett et al. (2001) have also used a real market behavior setting to analyze demand for toilet paper products, and have observed that some labels have had an impact (recycled paper), while other do not (unbleached paper). More recently, Vanclay et al. (2011) have found that adding a green label on a set of 37 products increased the market shares of the clean products by 4%, and that this shift was greater when green-labelled products were also the cheapest. In a paper based on an incentive-compatible experiment, Michaud et al. (2013) have identified a positive willingness-to-pay for two types of environmental attributes - an eco-label and a carbon footprint label - by analyzing results using a RUM framework. Other empirical studies also highlight that such labeling may also have a negative impact when individuals perceive that purchasing eco-products entails an increase in cost or risk, a decrease in product quality (Stern, 1999; Grankvist and Biel, 2001), or higher prices (Uusitalo and Oksanen, 2004), making the trade-off between private and public good attributes more explicit.

[2] Consider for example the recent boom in convenience goods exhibiting the "Marine Stewardship Council" label for sustainable seafood, or the "Forest Stewardship Council" for sustainable forestry, illustrate the recent spread of environmental labeling.

Our paper also follows the extensive literature on altruism and private provision of public goods (Olson, 1965; Sen, 1977; Andreoni, 1990; Kotchen, 2005). The literature identifies different sources of gains from public good provision. First, agents derive utility from the (shared) private benefits from the public good. In addition, benefits from public good participation can originate from pure altruism, when utility of others matter (Olson, 1965; Becker, 1974; Cornes and Sandler, 1986; Kotchen, 2005, 2006). But consumers might also derive direct utility from their own contribution, through a *warm-glow of giving* (Andreoni, 1990). This *impure altruism* theory suggests that there are additional private gains from intrinsic contributions to the public good, raising the potential impact of voluntary contributions (Brekke et al., 2003). In the context of food products, the frontier between private and public goods attributes is often blurred. For example, organic products may have public good benefits - using less pesticides, for example, helps protecting aquifers - but these are also associated with private benefits for the health of consumers. In our case, our label displays information on the carbon footprint of the products, which does not affect consumer choice through private benefits, since the carbon footprint is a global public good. By separating these two types of attributes, we manage to have a clearer picture of how private and public good characteristics each enter the consumers' choice process.

On the other hand, a subsidy (or a tax) on clean products contains both a monetary incentive and some information on the public good content of the products (here its carbon footprint). According to standard economic theory, a subsidy on low-carbon footprints is expected to have a stronger impact on consumer choices because it combines both types of incentives when information-based instruments contains only one. However, the literature on motivation crowding highlights that regulatory interventions adding a monetary reward when participation to public goods is voluntary can be counter-productive, as both stimuli can interact in non-trivial ways. Monetary instruments were shown to affect intrinsic motivation positively (crowding-in), but, more often, negatively (crowding-out) (see for example Frey and Jegen, 2001; Nyborg et al., 2006; Bowles, 2008). Our paper contributes to this literature by observing to what extent this mechanism is altered by the availability of close substitutes.

We find that, on average, all our instruments alter consumption patterns of respondents: cleaner products have a higher probability of being bought after our instruments are introduced.

We also confirm that the availability of close substitutes matters. When the low-footprint option is not too far from the initially purchased high-footprint counterpart, policy instruments perform better. In addition, we find that regulatory bans are more effective when the product category is more essential in the consumption basket because consumers are less likely to exit the market. Finally, our results suggest that the strength of motivation crowding mechanisms identified in Perino et al. (2014) also varies with the cost of switching: if high, consumers complying and purchasing clean options are less sensitive to the type of incentive provided. The remaining of this paper proceeds as follows. In Section 2, we describe the experimental setting, including the four different consumption goods we consider and the five policy treatments. In Section 3 and 4 we present our empirical specification and the results from our estimation. Section 5 concludes.

2 Experimental design

Data on consumer choices were collected in an experiment conducted in seven Sainsbury's supermarkets in the Greater London in February and March 2010. The experiment aimed to replicate real purchasing contexts of consumers. Consumers entering the supermarket were offered to participate voluntarily in a "university-sponsored grocery shopping study". The experiment was described as neutrally as possible, "studying how people make REAL LIFE grocery shopping decisions". No other information on the purpose of the experiment was provided. In particular, environmental motivations were not mentioned at any point during the recruitment phase to avoid self-selection of environmentally friendly respondents. Respondents also had to complete the task independently, without the help of the experimenter.

Participants made initial purchasing decisions on a computer at the entrance of the supermarket.[3] Those who intended to buy products selected for the experiment were then offered a £5 voucher to participate in the experiment, provided that they actually purchase the goods they chose in the experiment. The enforcement by making payment conditional on the actual purchase of goods selected allows to move away from a stated-preference framework, where the implications of stated choices do not have any consequence apart from potential social (dis)approval costs. This is a key condition of the experiment: data collected represent revealed

[3] Screenshots of the tasks are provided in Appendix B.

consumer preferences for sustainable food consumption, and indicate real market behavior. The compliance rate was 96%.

Respondents were enrolled only if they were about to purchase at least one high-footprint item (Cola in cans, butter, beef, or whole/semi-skimmed milk). In each of these categories, a range of options were offered to the consumers, each catering different tastes (private-good components) but also providing various public-good components. The goal is to identify what features matter in the decision-making process. The public good component here is the carbon footprint of the product over its life-cycle. Table 1 summarizes products and their public-good contents. Milk and butter were chosen for the importance they play in the UK food culture; Cola drinks were included to observe the impact of change on packaging; and meat was added due to the importance of this food category in the current debates on sustainability (FAO, 2006; Goodland and Anhang, 2009). More importantly, products were chosen such as to include a range of interaction of private and public good attributes. A change in the public good component (carbon footprint) implies changes in the private good components, and these vary across product categories. In the fresh meat category, the low-footprint product is chicken, whereas the high-footprint product is beef. The cost in terms of private preferences caused by the gain in public good will be high for consumers if the type of meat matters. In the case of Cola, only the packaging varies: the low-footprint product is Cola in 2L PET bottle, whereas the high footprint is Cola in aluminum cans. For spread (butter, margarine), additional attributes of the good are affected: butter and spread are not made from the same raw material - butter is made of milk, while spread is produced with vegetable oil. Finally, for milk, only the fat content changes the carbon footprint.[4] Furthermore, the importance of each product category in the consumption basket also varies. This is expected to impact the behavioral responses from the regulatory ban. When the preferred, dirty version is removed from the choice set, consumers are more likely to purchase a less-preferred version if the product category's presence in the consumption basket is important.

In a second step, participants who purchased at least one high-footprint product were randomly assigned to one of three treatments, allowing respondents to revise their initial choice. Five different instruments were provided: an information label showing the carbon footprints of

[4] A decrease for whole milk to skimmed milk decreases the carbon footprint in parallel

Table 1: Products and options

Product category	Options dirty/clean	Carbon footprint (public good)	Taste/brand (private good)
Cola	Aluminum can PET bottle	1,020g 500g	Coca Cola, Pepsi Cola, Diet Coke, Diet Pepsi, Coke Zero, Pepsi Max
Milk	Whole Semi-skimmed Skimmed	1,800g 1,600g 1,400g	Sainsbury's own brand fresh milk
Spread	Butter Margarine	11,900g 675g	Lurpak, Anchor, Countrylife, Kerrygold, Sainsbury's own brand
Meat	Beef Chicken	16,000g/kg of beef 5,000g/kg of chicken	Minced meat, casserole steak, braising steak chicken breast, mini chicken fillet, drumsticks

Notes: Cola, milk and spreads products all have the same weight across versions

products, a subsidy on the low-footprint product, a ban on the high-footprint product, and two neutrally-framed instruments. A neutral price change of the same amount than the subsidy, and a removal of the high-footprints goods, both for reasons unrelated to carbon footprints. Instruments are discussed more in details in the following sub-Sections. Finally, consumers were asked to purchase their final choice to get the £5 voucher. After the experiment, socio-demographic data on the respondents were collected. A total of 1225 shoppers completed the task (independently) and complied with all terms and conditions of the experiment, and are included in the sample, for a total of 1618 purchases of milk, 792 of butter, 624 of meat, and 666 of Cola. While our sample is not random, participants have diverse socio-economic backgrounds. Age varied from 21-80 years of age (mean: 37), and a wide range of incomes, educational backgrounds, family status and political, ethnic and religious groups were included, as summarized in Section 4.

2.1 Labeling

The labeling treatment consisted in a carbon footprint label following the design provided by the Carbon Trust UK. The label has the form of a stylized footprint and shows the amount of carbon dioxide equivalent GHG emissions caused over the life-cycle of the product in grams. To further analyze how respondents processed the information contained in the label, 3 different values of the carbon footprint were exhibited, each showing different values for the low and high footprint products, but without affecting the footprint ranking. This makes it possible to construct a continuous variable for the footprint, important in order to compare impacts across product categories. Values for the different versions of the label can be found in Appendix B. Simultaneously, nutritional information was also provided, to prevent respondents to guess the purpose of the experiment and behave accordingly.

2.2 Subsidy

The Subsidy treatment decreased the price of the low-footprint good. For example, in the case of Cola, respondents were told that "There has been a price change. Products in plastic bottles have a 5p discount due to a GOVERNMENT SUBSIDY received on account of its low carbon footprint". Consumers would understand that the change in prices was caused by a government intervention. In addition, the same labels than in the labeling treatment were provided. The value of the subsidy was calibrated on the externality created by the consumption of the products. Starting from an estimate for the social cost of carbon of $\pounds$70/tonne that is used in the UK (DEFRA, 2002; Pearce, 2003), we convert it into $\pounds/kg$ of product using the following conversion equation:

$$70\frac{\pounds}{tC} \times \frac{12}{44}\frac{tC}{tCO_2} \times 10^6\frac{gCO_2}{tCO_2} \times \Delta CF\frac{gCO_2}{kg} \tag{1}$$

were CF indicates the carbon footprint. In the case of milk and Cola, the resulting value was below 0.5 pennies, therefore invisible to consumers. Consequently, the resulting value was multiplied by 10 in the case of Cola, while in the case of milk, instead of the difference in carbon footprint (200g CO_2) the value used was the full carbon footprint of whole milk (1800g CO_2).[5] The final values of the subsidies were: $\pounds$ 0.05 for Cola; $\pounds$0.03 for semi-skimmed milk, or $\pounds$0.06

[5] This corresponds to the resulting value of the tax multiplied by 9.

for skimmed milk; £0.21 per kilo for meat (discounts depended on the weight of the chicken product chosen); and £0.43 for the switch from 0.5 kilos of butter to 0.5 kilos of margarine.

2.3 Neutral price change

The change in price in this treatment was identical to the subsidy, but the justification of the change in prices was presented as follows: "There has been a price change. Products in plastic bottles have a (value) discount because of a change in the price of materials". The change in prices was thus caused by market conditions unrelated to environmental dimensions, making this treatment 'environmentally neutral". This instrument will be then used to estimate the price elasticity of demand for each product category as a proxy for the substitutability of clean vs. dirty alternatives.

2.4 Ban

In this treatment all high-footprint alternatives were removed from the options available to the respondents, leaving them to choose only among the clean items. This change was justified as follows (in the case of Cola): "There has been a change in product availability. Products in can are not available because they have been BANNED by GOVERNMENT ORDER on account of their high carbon footprint". Two options were possible under that treatment. Either respondents would purchase the remaining low-footprint option, either they opt out, choosing "None of the above" option.

2.5 Exogenous removal

This treatment was identical to the ban treatment, but in this case, the removal was justified with the following statement (in the case of Cola): "There has been a change in product availability. Products are not supplied in cans on account of the lack of availability of the necessary materials". The utility derived from these two outside option were coded as an attribute in the next Sections, named "ban outside" and "removal outside".

Table 2: Options, attributes and instruments

	Cola	Milk	Spread	Meat
Nr. of options	13	4	11	7
Attribute 1	Can (=1)	Whole milk (=1)	Butter (=1)	Beef (=1)
Attribute 2		Semi-skim. milk (=1)		
Attribute 3	Coca-Cola (=1)		Lurpak (=1)	Protein (in g)
Attribute 4	Light (=1)		Sainsbury (=1)	Salt (in g)
Attribute 5	Zero (=1)		Anchor (=1)	Fat (in g)
Attribute 6			Kcal	
Attribute 7			Proteins (in g)	
Attribute 8			Carbohydrates (in g)	
Attribute 9			Fat (in g)	
Attribute 10			Salt (in g)	
Info	Diff. in carbon footprint of clean VS dirty option (in kg of CO_2)			
Subsidy	Decrease in price for clean options (in GBP cents)			
Dprice	Decrease in price for clean options (in GBP cents)			
Ban	Ban of the dirty options (=1)			
Removal	Removal of the dirty options (=1)			

Notes: Attribute 1 is directly related to the carbon footprint of the good (i.e. defines the 'dirty' product). Coca-Cola, Lurpak, Sainsbury, Anchor are brands.

3 Estimation strategy

Each product is described by an exhaustive set of characteristics or attributes: price, brand and nutritional features. These are summarized in Table 2. For instance, in the case of Cola, characteristics are packaging (2L PET bottle or cans), brand (Coca-Cola or Pepsi), and light or zero version. Attribute 1 is a categorical variable at the source of the high carbon footprint of the product. In the case of milk, because there are 3 different carbon footprints instead of 2, an additional attribute is used. In the second choice, product characteristics are manipulated by our treatments, altering the public good attributes (Label and Subsidy), prices (Subsidy and Neutral Price Change), or the number of options available to the respondent (Ban and Removal). In the case of the ban and the removal treatments, consumers can choose to opt out and exit the market. This resulting "outside option" enters the choice set as an additional option, with a corresponding utility.

3.1 MNL framework

Choices are analyzed with a standard MNL model, with the underlying behavioral foundation derived from Lancaster's RUM framework (Lancaster, 1966). In this setting, an individual n chooses an alternative i out of an exhaustive, finite set of mutually exclusive options if the utility of i is greater than any other alternatives in the choice set, with a probability given by:

$$Prob(U_{ni} > U_{nj}), \forall i \neq j \tag{2}$$

with $n = 1, \ldots, N$, $j = 1, \ldots, J$. Utility U_{nj} is decomposed into a deterministic part observed by the researcher, V_{nj}, and a random, unobserved part, ϵ_{nj}. Assuming that our utility function is linear in parameters, we obtain:

$$U_{ni} = V_{ni} + \epsilon_{ni} = \beta' X_{ni} + \epsilon_{ni} \tag{3}$$

where X_{ni} is a vector of alternative-specific covariates. In consequence, the probability that individual n chooses alternative i is:

$$P_{ni} = Prob(\epsilon_{ni} - \epsilon_{nj} < V_{ni} - V_{nj}), \forall i \neq j \tag{4}$$

i.e. if the unobserved part of utility overcompensates the (potential) difference in the observable utility. Assuming further that ϵ_{ni} is iid and follows a Gumbel distribution, we have the choice probabilities from the MNL specification:

$$P_{ni} = Prob(Y_n = i) = \frac{e^{\beta' x_{ni}}}{\sum_j e^{\beta' x_{nj}}} \tag{5}$$

The ratio of choice probabilities depends only on attributes of alternatives i and j, the so-called independence of irrelevant alternatives (IIA). As robustness check, we estimate a Mixed logit model (MXL) that allows to relax the assumption of independence of irrelevant alternatives often biasing results in discrete choice estimations (McFadden and Train, 2000). Choice probabilities are:

$$P_{ni} = \int \frac{e^{x'_{ni}\beta}}{\sum_{j=1}^{J} e^{x'_{nj}\beta}} f(\beta|\theta) d\beta \tag{6}$$

As can be shown, the ratio of choice probabilities P_{ni}/P_{nj} in the case of MXL depends also on attributes of alternatives other than i or j, thereby avoiding the assumption of IIA, since the denominators in the logit formula are inside the integrals, and therefore are not cancelled out.[6] We estimate our model by maximum-likelihood, with the following simple log-likelihood function:

$$logL = \sum_{n=1}^{N} \sum_{j=1}^{J} d_{nj} \log Prob(Y_n = j) \tag{7}$$

where d_{nj} is an indicator function equal to 1 if $Y_n = j$ and zero otherwise Our empirical specification allows to identify choice patterns as triggered by our instruments free of other variations, as we control for product characteristics entering the choice. However, because a change in the attribute set affects the probabilities of all options, the vector of estimated coefficients is not directly tied to the marginal effects. In addition, the estimated coefficients are not separately identified from the variance of the error term, so that they cannot be directly compared across models. We thus need to consider specific measures from the coefficients obtained from the MNL estimation to compare coefficients across product categories. We first calculate elasticities of probability of choices w.r.t. a change in a given attribute from a given alternative i:

$$E_{iz_{ni}} = \frac{\partial P_{ni}}{\partial z_{ni}} \frac{z_{ni}}{P_{ni}} = \frac{\partial V_{ni}}{\partial z_{ni}} (1 - P_{ni}) \bar{z}_{ni} = \beta_z \bar{z}_{ni} (1 - P_{ni}) \tag{8}$$

Second, we calculate the odds ratios, measuring the marginal impact of treatments on the ratio of the probabilities of choosing each option:

$$OR_{jk} = \frac{e^{\beta' x_{nj}+1} / \sum_j e^{\beta' x_{nj}+1}}{e^{\beta' x_{nj}} / \sum_j e^{\beta' x_{nj}}} \tag{9}$$

where we index utility by pre- and post- treatments (t and $t+1$).

[6] See (Train, 2009) for a detailed description of the Mixed Logit Specification

3.2 Measures of substitutability

From this framework, we derive two measures of substitutability based on our neutrally framed treatments. We first use the behavioral impact of a change in the price of clean alternatives - in other words, a price elasticity - as an implicit measure of the substitutability of clean vs. dirty options. Economic theory informs us that the availability of close substitutes has a direct impact on the price elasticity of demand. If clean substitutes offered to consumers for a given product category are considered as close, the price elasticity of demand for dirty goods will be high. A large behavioral impact of the neutral price change treatment will thus reflect that clean vs. dirty alternatives are considered close substitutes.

In our case, the cost of switching in terms of private preferences is expected to be lower in the case of Cola (Cola in 2L PET bottle vs. Cola in cans) and milk (decrease in fat content) than in the case of meat (chicken vs. beef) or spread (butter vs. margarine). To measure price elasticity, we use the coefficient on the "neutral price change" treatment rather than simply the coefficient on the price attribute for several reasons. First, because in a revealed preference setting, attributes of products cannot vary freely. This causes the variance of the attributes of interest to be constrained and might imply a high level of collinearity across attributes, making estimates more sensitive. Second, because a temporary change in price can have a different impact than the standard price because of salience and mental accounting.

The second measure is generated from our exogenous removal treatment. In this treatment, we observe how consumers behave when their (preferred) dirty version is removed from the choice set. We recover a measure of the utility derived from the outside option if consumers drop out of the market. The rationale is that if utility of the clean (non-preferred) version i is too far from the preferred dirty version and does not reach minimal threshold, i.e. if they are not considered substitutes, the individual drops out of the market. However, this statistic also captures the importance of the product category in the consumption basket. All else equal, consumers are more likely to opt out when their preferred version is removed from the choice set if the product category is non-essential, even if the remaining option is considered a close substitute.

4 Data and estimation results

4.1 Descriptive statistics and observed choices

Table 3 describes the demographic variables in our sample. As we can see, demographic variables are comparable across products. This is important because respondents self-select into each product category, so that our results could be driven by consumer heterogeneity between product subsamples. Respondents initially purchasing each product could have distinctive features - age, income, education, or costs of processing information - that could affect the effectiveness of our treatments, whilst unrelated to product characteristics.

Table 4 shows the number of 'clean' purchases across products and treatments before (t) and after the treatment ($t+1$). In the case of the ban and the removal treatments, respondents could either purchase the clean version or exit the market (i.e. choose the outside good). Preliminary results suggest that instruments performed better for the Cola and milk categories, where we observe the biggest increase in clean purchases. The case of semi-skimmed milk is particular, because the carbon footprint is not binary - high or low - but continuous. The impact of our treatments is dual. Respondents switching to cleaner options can move from whole to semi-skimmed, or from semi-skimmed to skimmed, having an ambiguous impact on the market share of the semi-skimmed option.

Furthermore, we see that the initial market shares of dirty products are important - ranging from 49% for butter, to 62% for Cola in cans, 80% for beef and 88% for whole and semi-skimmed milk. These figures show that dirty products account for a significant share of the market of each product categories, suggesting a role to play for policy intervention.

Table 3: Demographic variables by product subsample

Variable	Obs.	Mean	Std. Dev.	Min	Max
Cola subsample					
Age	346	33.62	11.6	18	72
Children in the Household	346	.630	1.036	0	6
Male dummy	346	.439	.497	0	1
Income category	346	3.881	2.763	1	9
Education	346	1.766	.765	1	3
Env. Assoc. dummy	346	.014	.119	0	1
Christian	346	.431	.49	0	1
Muslim	346	.133	.34	0	1
Non-white	322	.451	.50	0	1
Milk subsample					
Age	825	37.07	12.03	18	80
Children in the Household	825	.632	1.00	0	6
Male dummy	825	.358	.480	0	1
Income category	825	4.024	2.792	1	9
Education	825	1.802	.733	1	3
Env. Assoc. dummy	825	.035	.184	0	1
Christian	825	.470	.50	0	1
Spread subsample					
Age	431	38.26	12.24	18	79
Children in the Household	431	.649	1.011	0	6
Male dummy	431	.336	.473	0	1
Income category	431	3.807	2.684	1	9
Education	431	1.789	.747	1	3
Env. Assoc. dummy	431	.042	.200	0	1
Meat subsample					
Age	322	38.39	12.22	18	79
Children in the Household	322	.540	1.01	0	6
Male dummy	322	.373	.484	0	1
Income category	322	3.901	2.641	1	9
Education	322	1.748	.729	1	3
Env. Assoc. dummy	322	.031	.174	0	1
Christian	322	.556	.50	0	1
Muslim	322	.027	.16	0	1

Notes: Education is coded as: 1 – Non-university education or equivalent; 2 – Graduate level (including current undergraduate students) - and any other university diploma; and 3 – Postgraduate level (including current postgraduate students). Income is coded from 1–8, from 15'000 to 75'000 pounds annually.

Table 4: Consumption patterns by product/instrument

		Info	Subsidy	Price	Ban	Removal
Cola	Purchases	62	64	63	68	76
	Clean t	23	20	17	30	35
	Clean $t+1$	36	32	44	61	66
	Changes	13	12	27	31	31
Spread	Purchases	83	71	82	76	84
	Clean t	42	40	32	46	42
	Clean $t+1$	52	45	42	67	75
	Changes	10	5	10	19	33
Meat	Purchases	56	63	69	68	56
	Clean t	7	13	15	13	14
	Clean $t+1$	18	19	23	51	44
	Changes	11	6	8	38	30
Milk	Purchases	162	147	168	157	175
	Skimmed t	23	9	14	21	24
	Skimmed $t+1$	35	16	24	103	95
	Changes	12	7	10	82	71
	Semi-skimmed t	84	79	97	93	85
	Semi-skimmed $t+1$	83	77	99	0	0
	Changes	-1	-2	2	-60	-40
	Whole t	55	59	57	43	66
	Whole $t+1$	44	54	45	0	0
	Changes	-11	-5	-12	-22	-31

Notes: For the "ban" and "removal" treatments, respondents who did not chose the clean alternative exited the market by choosing the outside good.

4.2 Econometric results

We now turn to the estimation of a discrete choice model specified in equations (2) to (9). Once estimated, this model allows us to 1) observe the impact of the treatments across products free of other variation, 2) obtain a measure of substitutability directly estimated by the data, and 3) evaluate how the effectiveness of policy instruments depends on the options available to the consumer.

Estimation results from the MNL model are reported in Table 5. In our experiment, instruments are calibrated on a level of public good associated with each option that varies in magnitude across product categories.[7] To make instruments comparable, we code them as continuous variables. Their coefficients are to be interpreted as the impact of a given difference in kilogram of CO_2 footprint between the clean and the dirty version on a label, and of a given GBP cent of monetary instrument, which is comparable across the different regressions. The information treatment is thereby coded as the absolute difference of the carbon footprint associated with clean and the dirty versions of each product, measured in kilograms of CO_2.[8] In the case of milk, where the carbon footprint differs for whole, semi-skimmed and skimmed milk, the label treatment variable captures the difference with the footprint of the 'dirtiest' option. Similarly, the monetary treatments - subsidy ('subs') and neutral price change ('dprice') - are coded in GBP cents. Finally, the ban and the removal treatments offer respondents the possibility to exit the market in their second choice. These treatments are coded as categorical variables, and the utility of the 'outside' good is captured by two additional variables ('ban outside') and ('remov outside').

Results confirm that most treatments have a statistically significant impact on the probability of choosing clean vs. dirty options, with the expected sign: treatments increase the market share of the clean options. The only exception, where variables associated with each treatment are not statistically significant at conventional levels, the labeling treatment for meat products and the neutral price change for spreads. The coefficients on the dirty attributes inform us about the average preference for products with a high carbon footprint. Dirty attributes all yield

[7] Instruments levels are found in Table 1.

[8] Recall that the labeling treatment features three different assumptions about the carbon footprint of each product.

Table 5: Estimation results – Multinomial logit model

	Cola (1)	Milk (2)	Spread (3)	Meat (4)
Info label	1.67***	.948***	.050**	.024
	(.427)	(.184)	(.022)	(.023)
Subs	.135***	.108**	.012**	.024*
	(.049)	(.026)	(.005)	(.013)
Dprice	.303***	.227***	.0004	.031***
	(.056)	(.039)	(.005)	(.012)
Ban	-19.10***	-23.43***	-17.09***	-18.04***
	(.164)	(.105)	(.147)	(.220)
Removal	-19.07***	-20.61***	-17.09***	-17.85***
	(.157)	(.110)	(.150)	(.230)
Ban outside	.274	-.646***	3.656***	3.912***
	(.438)	(.168)	(.615)	(.600)
Remov. outside	.552	-.172	3.546***	3.985***
	(.380)	(.152)	(.619)	(.616)
Price	.000		-.017***	-.001
	(.001)		(.003)	(.0004)
Attribute 1	.602***	1.877***	.998**	1.21***
(DIRTY VS CLEAN)	(.232)	(.031)	(.489)	(.190)
Attribute 2		2.190***		
(DIRTY VS CLEAN)		(.104)		
Attribute 3	1.71***		2.11***	.129***
	(.146)		(.347)	(.016)
Attribute 4	-.677***		-2.24**	-6.77***
	(.119)		(.521)	(1.25)
Attribute 5	-1.69***		.140	.221***
	(.173)		(.303)	(.020)
Attribute 6			.221	
			(.225)	
Attribute 7			-5.78**	
			(2.33)	
Attribute 8			.751	
			(1.50)	
Attribute 9			-1.88	
			(2.02)	
Attribute 10			.321	
			(.538)	
Respondents	333	809	396	312
Wald chi^2	50559.61	132556.82	48777.62	35191.07
Prob > chi^2	0.00	0.00	0.00	0.00
Pseudo R^2	0.2414	0.3098	0.1642	0.2491

Notes: standard errors in parenthesis, clustered at the respondent level. p***$\leq$ 0.01, p**, $\leq$0.05, p*$\leq$0.1. Instruments are coded in kg of CO_2 and in GBPcents. The list of attributes can be found in Table 2.

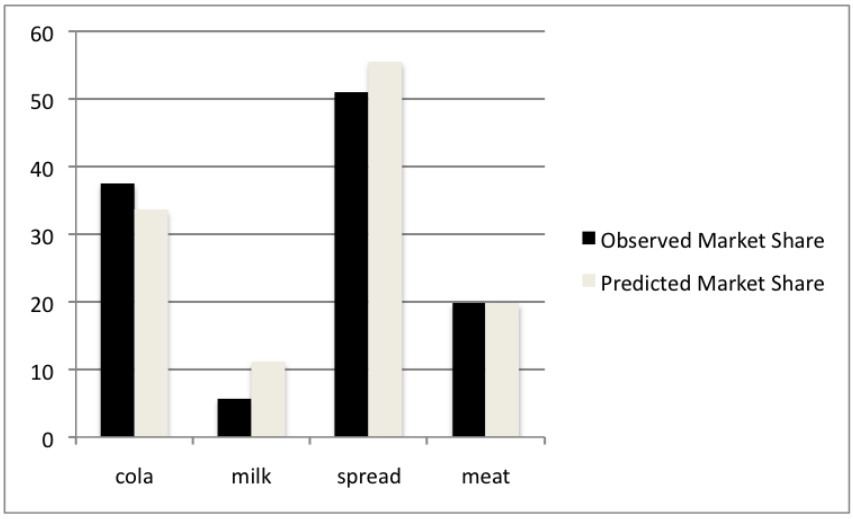


Figure 1: Predicted and observed market shares of clean products (%)

positive utility, resulting in large market shares of dirty products.[9] These results highlight the existence of an inherent trade-off between private and public good attributes, thus suggesting a need for policy intervention. More generally, many variables capturing preferences for products' attribute are statistically significant, suggesting that the model provides a good account of observed choices. This is confirmed by comparing predicted market shares of clean products with the initial market shares observed from our sample (Figure 1). Indeed market shares for clean products simulated from the estimation are very close to the initial market shares reported in Table 4.

As robustness check, we estimate a Mixed Logit Model as described in equation (6). We use 200 Halton draws, and use products attributes as random covariates. Moreover, the number of parameters to be estimated is increased, reducing the number of degrees of freedom, potentially affecting the precision of our estimates. That kept in mind, results in Table 8 in Appendix A do not differ greatly from the standard MNL, suggesting that our estimates are robust to IIA.

4.3 Measures of Substitutability

We now calculate our measures of substitutability from the estimates in Table 5. As mentioned previously, to compare results across equations, we present in Table 6 the elasticities of purchasing probabilities in the first matrix and report coefficients as Odds Ratio in the second matrix, for

[9] This result is consistent with the market shares observed in Table 4

each of our two measures of substitutability.[10] A large behavioral impact of our price treatment would reflect high substitutability between the clean and the dirty versions. A change in the price of 1% is translated in an increase in purchasing probability of 1.40% in the case of Cola, 0.77% for milk, 0.56% for meat and 0.01% for spread. For the Odds Ratios, an increase of one GBP cent results in a change in the ratio of choice probability of 1.354 for Cola, 1.255 for milk, 1.032 for meat and 1.000 for spread (no impact). The elasticities as well as the coefficient on the Odds Ratio thus suggest that the price elasticity is highest for the Cola category, followed by milk, fresh meat and finally by spread, where the impact on the odds ratio is close to none.

Results for our second measure of substitutability are by and large similar. Recall that the interpretation for this treatment is opposite: a high figure would reflect a high value of the outside option, suggesting that consumers do not consider the remaining option a substitute 'close enough'. As can be seen, consumers are more likely to opt out when their preferred version is removed from the choice set in the case of fresh meat and spread, our non-substitutable product categories, than for cola and milk, where the coefficients on the outside option becomes statistically insignificant. The magnitude of the coefficients of the Odds Ratio for the non-substitutable product categories seem very high. Whereas such differences could seem puzzling, it simply reflects the fact the initial market share of the outside option is close to zero by definition. Because we measure a ratio of probabilities, even a small impact will result in high figures because initial market shares are small. As soon as the attribute has an impact, this impact will be large.

Furthermore, we see that substitutability as measured by the outside option is lower for the Cola category than for milk, though the criterion of price elasticity suggests the opposite. This captures the importance of the product category in the consumption basket. When the preferred version is removed, consumers are more likely to purchase a less-preferred version if the product is essential - Cola is expected to be less essential than milk. A similar effect is observed for non-substitutable product categories: spread seems to be more essential than fresh meat, probably due the high number of end-uses associated with spreads.

From this analysis, we conclude that, as expected, two product categories - Cola and milk - have substitutes perceived as close, and two perceived as less close - spread and fresh meat.

[10] Recalling equation (9), a coefficient higher than one (between zero and one) means that the covariate increases (decreases) the probability of choice.

Table 6: Measures of Substitutability of Clean vs. Dirty Versions

	Cola	Milk	Spread	Meat
Elasticities of Purchasing Probabilities				
Price elasticity	1.399***	.7657***	.0148	.560***
	(.056)	(.039)	(.005)	(.012)
Removal - outside option	.510	-.1289	3.223***	3.415***
	(.380)	(.152)	(.619)	(.616)
Coefficients as Odds Ratio				
Price elasticity	1.354***	1.255***	1.000	1.032***
	(.076)	(.049)	(.005)	(.012)
Removal - outside option	1.736	.842	34.67***	53.77***
	(.659)	(.127)	(21.45)	(33.11)
Respondents	333	809	403	312

Notes: p***$\leq$ 0.01, p**$\leq$0.05, p*$\leq$0.1. Standard errors are those of the coefficient used for the calculations. Price elasticity is based on the price elasticity coded in GBP cent and calculated at the mean of prices. The outside option is based on the coefficient on the outside option as categorical variable

4.4 Effectiveness of Policy instruments

In this section, we explore whether the availability of close substitutes translates into higher effectiveness of our carbon footprint label, our subsidy calibrated on the external cost of carbon and our Governmental ban on dirty products. Results are found in table 7. In the first specification, treatments are coded according to the level of externality: the information label is coded in kilograms of CO_2 - the difference of CO_2 footprint between the clean and the dirty version - and the monetary instruments in GBP cents. Again, this allows comparing the impact of instruments across product categories, because the level of the public good associated with each product varies. Differences in effectiveness across product categories could be triggered by differences in the level of externality rather than in the availability of substitutes, because instruments are calibrated on these.[11]

[11] Figures in spec. 1 are to be interpreted as the average impact on the ratio of choice probabilities per kilogram of CO_2 and per GBP cent for the label and the subsidy/change in price respectively

Important differences across products are evident: instruments are more effective for product categories where clean versions were identified as close substitutes, namely Cola and milk, than for spread and fresh meat. All else equal, a carbon footprint label and a subsidy on cleaner options perform better when the cost of switching in terms of private preferences is low. Similarly, a subsidy (in GBP cents) has a larger behavioral impact for Cola and milk than for spread and meat. These results on the role of the elasticity of substitution differs slightly with the results found in Perino et al. (2014). These differences arise from the fact that the MNL specification allows to control explicitly for product characteristics that determine the market shares of products. By including all choices in a single estimation, we control for the underlying preference for dirty products and observe the impact of instruments free of other variations.

The behavioral impact of regulation ('Ban - outside option') also seems to depend on whether the product category is essential. Consumers exit the market on average less when a regulation bans dirty options from the choice set when close substitutes are available. Furthermore, the utility derived from the outside option is lower for milk than for Cola: even if Cola products are considered closer substitutes, consumers drop out of the market on average more than for milk due to its importance in the consumption basket. Similarly, for low-substitute product categories, the coefficient from the outside option is higher for fresh meat than for spreads, reflecting the fact that spreads is more essential than fresh meat.

In the second specification, we recode our treatment as categorical variables. This provides a way to compare policy instruments within each product category in order to identify potential crowding effects.[12] As mentioned previously, a subsidy combining a monetary incentive with information about the public good content of products is expected to have a greater impact than an information label alone according to traditional economic theory. However, in our case, the monetary and the voluntary incentives are not simply additive. The information label has a higher impact on the purchasing probability of clean goods than a subsidy calibrated on the same level of externality for 3 out of 4 products, which we interpret as motivation crowding: the additional monetary incentive of the subsidy seems to crowd out the intrinsic motivation as triggered by the label.

[12] In the case of milk, because the treatment is continuous, 2 dummies had to be added. Treatments for skimmed milk are more effective than for semi-skimmed milk because respondents could move directly from whole milk to skimmed

Table 7: Effectiveness of Policy Instruments

		Cola	Milk	Spread	Meat
Specification 1 - Across Product Categories					
Info	OR	5.313***	2.580***	1.051**	1.024
		(2.27)	(.290)	(.023)	(.023)
Subsidy	OR	1.145***	1.113***	1.012**	1.024*
		(.056)	(.030)	(.005)	(.013)
Ban - outside option	OR	1.315	.524***	38.70***	50.03***
		(.575)	(.09)	(23.8)	(30.49)
Specification 2 - Within Product Category					
Info	Coeff.	1.01***		.491**	.677**
		(.247)		(.213)	(.294)
Infosemi	Coeff.		.362**		
			(.173)		
Infoskim	Coeff.		1.96***		
			(.207)		
Subsidy	Coeff.	.683***		.512**	.570**
		(.488)		(.229)	(.261)
Subs. semi	Coeff.		.082		
			(.163)		
Subs. skim	Coeff.		.970***		
			(.272)		
Respondents		333	809	403	312

Notes: standard errors in parenthesis, clustered at respondent level. p***$\leq$ 0.01, p**$\leq$0.05, p*$\leq$0.1. In specification 1, instruments are coded in kilograms of $C0_2$ and GBP cents. In specification 2, treatments are coded as categorical (dummy) variables. Coeff. magnit. in spec. 1 is to be interpreted across products, while spec. 2 across treatments

More interestingly, the difference between the behavioral impact of the label and the subsidy is greater for Cola and milk, i.e. where substitutes are close. In other words, when substitutes are close, a monetary incentive crowds out intrinsic motivation relatively more. Regardless of the incentive, choices cannot be easily redirected by policy intervention when the utility derived from the clean option is too low. This translates first into low effectiveness of policies for those product categories *on average*, but it also lowers motivation crowding effects, because

choices are then determined by preferences. The cost of switching seems to act as a 'preference constraint'. When consumers consider the cost of switching as high, preferences are binding and thus instrumental in determining choices. In contrast, when the preference constraint is not binding, consumers are more indifferent between clean and dirty options, such that motivation crowding effects begin to be observed.

5 Conclusion

While there is an increasing amount of evidence about the impact of environmental policy through policy experiments, controlled experiments comparing alternative policy instruments to manage public goods in a "real" consumption choice setting is scarce. In addition, there is little evidence about how similar policy instruments influence consumption choice across different products and whether the existence of 'clean' products that are close substitutes will impact the effectiveness of alternative policy instruments.

Our study has allowed to analyze and compare different policy instruments to manage public goods in a controlled experiment, and see how they perform across a range of frequent-purchase products. Our results suggest that, on average, information labels, monetary incentives and regulatory bans increase the market share of cleaner goods. Instruments result in a change in predicted market share from 16-24% depending on the policy instrument. Differences across products were found to be important. Using two measures of substitutability of clean vs. dirty alternatives estimated from our model - namely a price elasticity and a measure of the propensity of consumers to exit the market when their preferred version is banned - we established that products with clean alternatives that are close substitute will enhance the change in consumption behavior. If environmentally-friendly options are too far from the preferred option, monetary instruments and information provision favoring voluntary contributions are found to be less effective. Moreover, regulatory interventions banning dirty products result in less consumers exiting the market in the presence of close substitutes and if the product category is essential in the consumption basket. The presence of close substitutes also appeared to alter motivation crowding mechanisms, which were found to be stronger for product categories where close substitutes were available, through a 'preference' constraint.

Some final aspects of our study have to be bore in mind. First, frequent purchases of day-to-day commodities tend to be carried out by habits (Ouellette and Wood, 1998). Day-to-day commodities, of relatively common occurrence, are carried out in familiar and stable environments, most often with a "satisfactory result" objective. Habits imply that less time and effort are devoted to the decision process (Verplanken et al., 1997). Individuals with strongly habit-controlled behavior have been shown to allocate less time to the decision process, and may therefore be less sensitive to new attributes entering the decision process, possibly affecting the probability that consumers switch to products with lower carbon footprint. Second, our study considers carbon labels, signaling a pure public good, while many environmental labels for food products - for example bio labels - tend to combine both private good and public good benefits. This has allowed a clearer understanding of the role of private and public good attributes, but comes at the cost of limiting the generalization of our results. Finally, our experimental design is limited to short term mechanisms. Policy instruments to regulate the public good could have additional impacts on consumers' choices in the longer term by directly altering alter social norms, which is not captured in our framework.

Appendix A

Table 8: Estimation results – Mixed logit model

	Cola (1)		Milk (2)		Spread (3)		Meat (4)	
	Coeff.	S.D.	Coeff.	S.D.	Coeff.	S.D.	Coeff.	S.D.
Info label	1.64***		.934***		.052**		.028	
	(.433)		(.107)		(.024)		(.025)	
Subs	.132***		.149***		.014**		.029**	
	(.050)		(.025)		(.006)		(.014)	
Dprice	.302***		.215***		.005		.044***	
	(.056)		(.022)		(.006)		(.014)	
Ban	-26.0***		-25.4***		-24.5 ***		-24.0 ***	
	(.164)		(.106)		(.795)		(.342)	
Removal	-25.9***		-24.9***		-24.6***		-24.0 ***	
	(.158)		(.112)		(.767)		(.354)	
Ban outside	.674		-.604***		7.14***		3.71***	
	(.642)		(.168)		(1.64)		(.458)	
Remov. outside	.981*		-.131		7.71***		3.69***	
	(.564)		(.152)		(1.93)		(.464)	
Price	-.0006				-.031***		-.000	
	(.001)				(.006)		(.000)	
Attribute 1	.695***		.206***	-0.01	-.666		1.22***	
	(.239)		(.009)	(.050)	(1.013)		(.224)	
Attribute 2	3.40***	3.02***			1.606	-5.76**	.105***	.000
	(.428)	(.470)			(1.029)	(1.045)	(.015)	(.005)
Attribute 3	-2.99***	6.05***			-6.747	-5.88*	-5.90***	3.24
	(.618)	(1.07)			(4.472)	(3.28)	(1.42)	(2.15)
Attribute 4	-7.24***	6.16***			-2.19***	5.61***	.222***	.17***
	(1.45)	(1.04)			(.790)	(.944)	(.021)	(.022)
Attribute 5					-.331	.009***		
					(.343)	(.002)		
Attribute 6					-.485			
					(4.52)			
Attribute 7					-1.33			
					(1.84)			
Attribute 8					3.19			
					(3.08)			
Attribute 9					2.82**			
					(1.15)			
AIC	2281.1		3600.4		2819.6		1799.3	
BIC	2370.7		3651.5		2945.0		1878.6	
Wald chi2	92362.8		193432.0		14761.9		14761.8	
Prob> chi2	0.00		0.00		0.00		0.00	

Notes: Standard errors in parenthesis. p***$\leq$ 0.01, p**, $\leq$0.05, p*$\leq$0.1, clustered at the respondent level. Instruments are coded in kg of CO_2 and in GBPcents. Random coefficients are attributes of products except price variable and Attribute 1. For butter, some additional attributes (prot, carb, fat, salt) are treated as non-random variables to ensure convergence.

Appendix B Screen shots of the experiment

Appendix B.1 Initial purchase and treatments for Cola

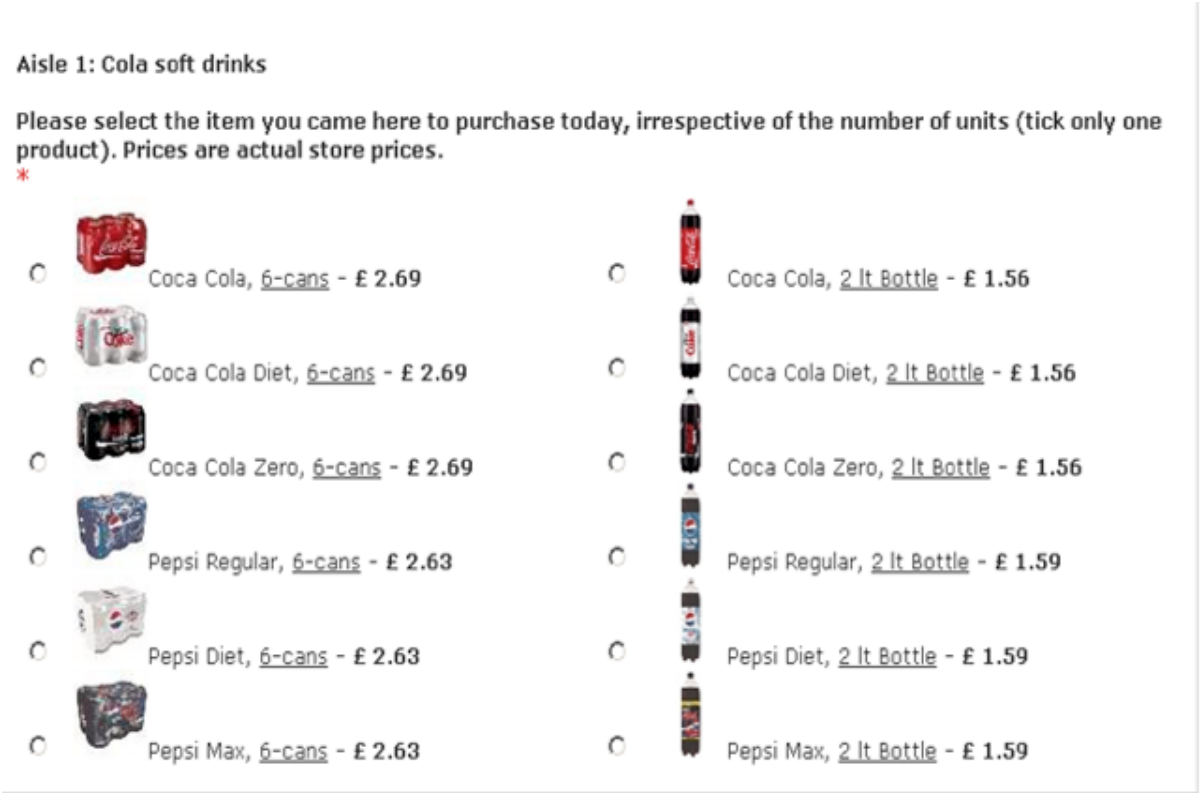


Figure 2: Initial purchase

Exit Survey »

Questions marked with a * are required

NUTRITIONAL INFORMATION

	Coke	Diet Coke	Coke Zero	Pepsi	Pepsi Max	Diet Pepsi
	per 100 ml	*per 100 ml*	*per 100 ml*	*per 100 ml*	*per 100 ml*	*per 100 ml*
Energy (kCal)	42	0.5	0.5	42	0.3	0.4
Protein (g)	0.0	0.0	0.0	0.0	0.1	0.0
Carbohydrate (g)	10.6	0.0	0.0	11.0	0.0	0.0
Fat (g)	0.0	0.0	0.0	0.0	0.0	0.0
Salt (g)	0.0	0.0	0.0	0.0	0.0	0.0

CARBON FOOTPRINT INFORMATION

Drink in Plastic bottles

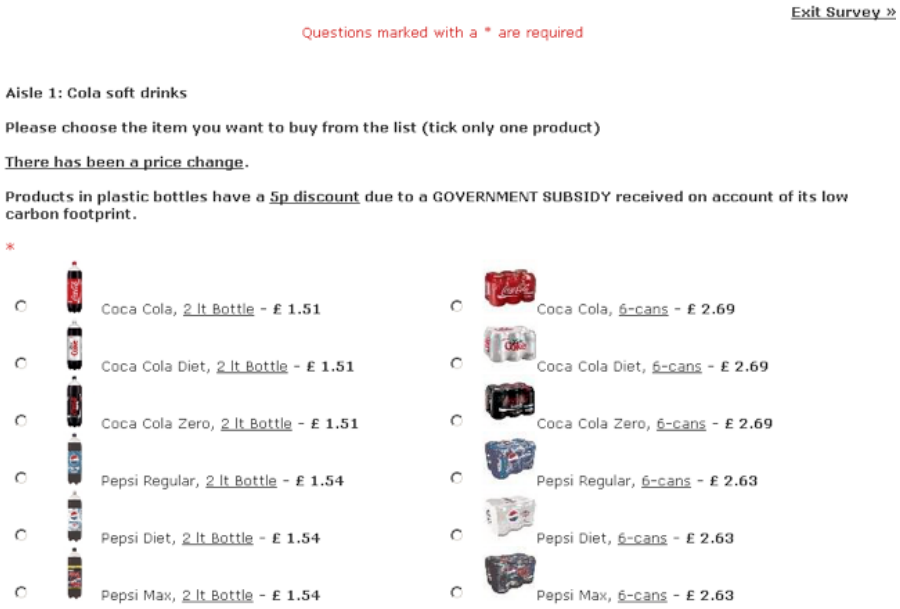
Drink in cans

Aisle 1: Cola soft drinks

Please choose the item you want to buy from the list (tick only one product)
*

- Coca Cola, 2 lt Bottle - **£ 1.69**
- Coca Cola Diet, 2 lt Bottle - **£ 1.69**
- Coca Cola Zero, 2 lt Bottle - **£ 1.69**
- Pepsi Regular, 2 lt Bottle - **£ 1**
- Pepsi Diet, 2 lt Bottle - **£ 1**
- Pepsi Max, 2 lt Bottle - **£ 1**
- Coca Cola, 6-cans - **£ 2.85**
- Coca Cola Diet, 6-cans - **£ 2.85**
- Coca Cola Zero, 6-cans - **£ 2.85**
- Pepsi Regular, 6-cans - **£ 2.75**
- Pepsi Diet, 6-cans - **£ 2.75**
- Pepsi Max, 6-cans - **£ 2.75**

Figure 3: Labeling treatment



Exit Survey »

Questions marked with a * are required

Aisle 1: Cola soft drinks

Please choose the item you want to buy from the list (tick only one product)

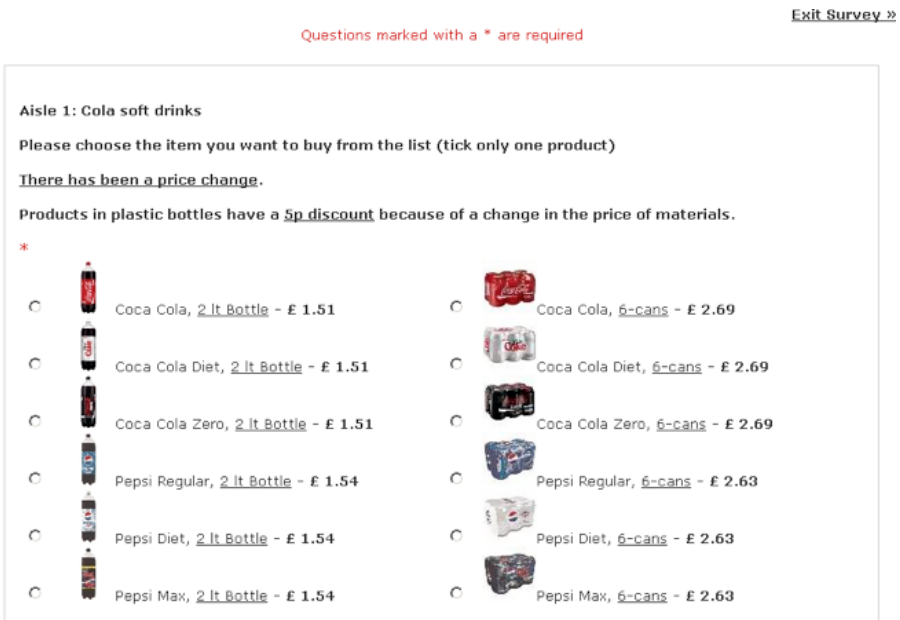
There has been a price change.

Products in plastic bottles have a 5p discount due to a GOVERNMENT SUBSIDY received on account of its low carbon footprint.

*

- Coca Cola, 2 lt Bottle - £ 1.51
- Coca Cola Diet, 2 lt Bottle - £ 1.51
- Coca Cola Zero, 2 lt Bottle - £ 1.51
- Pepsi Regular, 2 lt Bottle - £ 1.54
- Pepsi Diet, 2 lt Bottle - £ 1.54
- Pepsi Max, 2 lt Bottle - £ 1.54
- Coca Cola, 6-cans - £ 2.69
- Coca Cola Diet, 6-cans - £ 2.69
- Coca Cola Zero, 6-cans - £ 2.69
- Pepsi Regular, 6-cans - £ 2.63
- Pepsi Diet, 6-cans - £ 2.63
- Pepsi Max, 6-cans - £ 2.63

Figure 4: Subsidy treatment



Exit Survey »

Questions marked with a * are required

Aisle 1: Cola soft drinks

Please choose the item you want to buy from the list (tick only one product)

There has been a price change.

Products in plastic bottles have a 5p discount because of a change in the price of materials.

*

- Coca Cola, 2 lt Bottle - £ 1.51
- Coca Cola Diet, 2 lt Bottle - £ 1.51
- Coca Cola Zero, 2 lt Bottle - £ 1.51
- Pepsi Regular, 2 lt Bottle - £ 1.54
- Pepsi Diet, 2 lt Bottle - £ 1.54
- Pepsi Max, 2 lt Bottle - £ 1.54
- Coca Cola, 6-cans - £ 2.69
- Coca Cola Diet, 6-cans - £ 2.69
- Coca Cola Zero, 6-cans - £ 2.69
- Pepsi Regular, 6-cans - £ 2.63
- Pepsi Diet, 6-cans - £ 2.63
- Pepsi Max, 6-cans - £ 2.63

Figure 5: Neutral price treatment

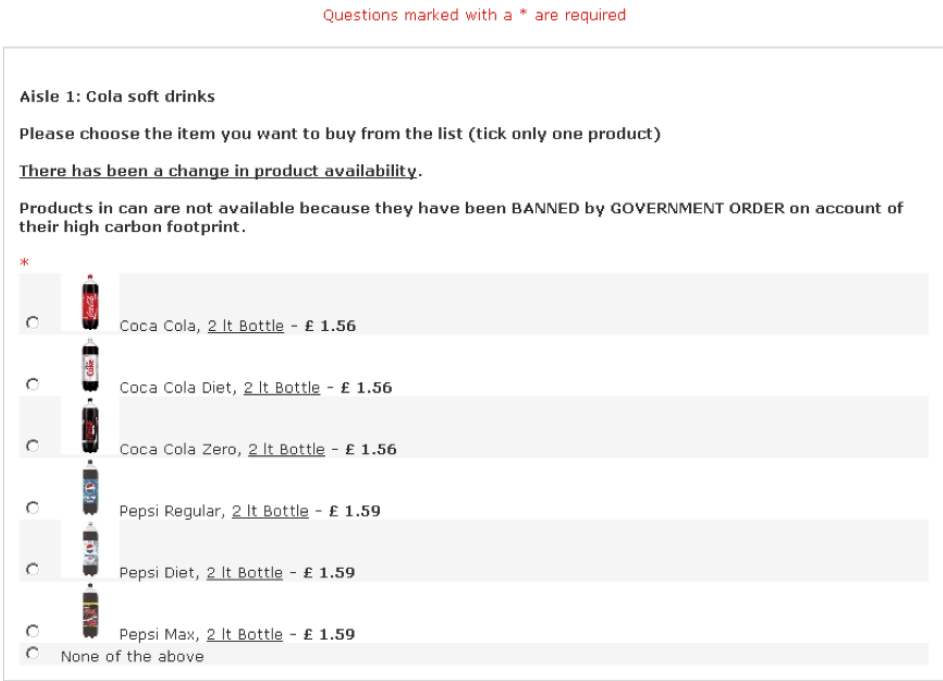


Figure 6: Governmental ban treatment

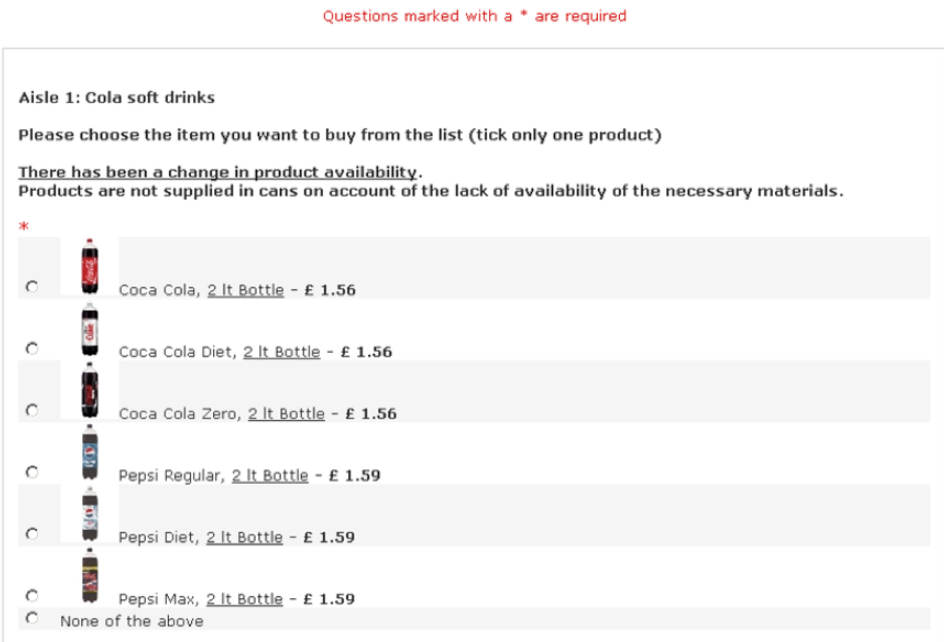


Figure 7: Neutral removal treatment

Appendix B.2 Carbon footprint labels: versions 1-3, by product

Figure 8: Carbon footprints labels for Cola

Figure 9: Carbon footprints labels for Milk

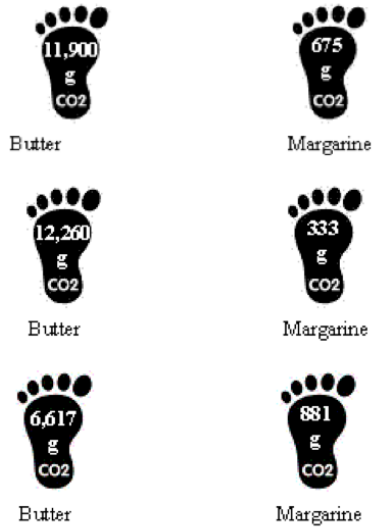


Figure 10: Carbon footprints labels for Spread

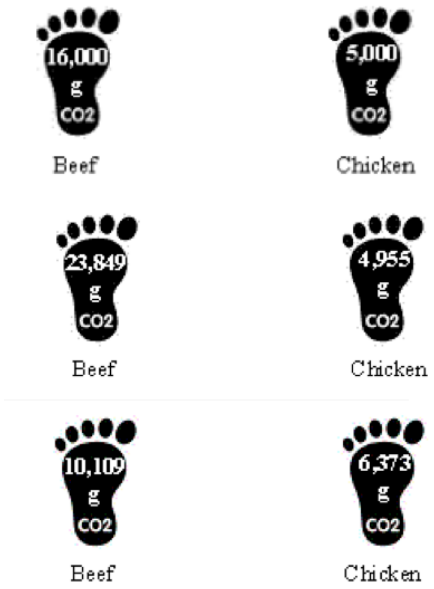


Figure 11: Carbon footprints labels for Fresh Meat

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